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Specification

Method for Evaluating the Signals of an Electronic Image Sensor During Pattern Recognition of Image Contents of a Test Piece

The invention relates to methods for signal evaluation of an electronic image sensor in the course of pattern recognition of the image contents of a test body in accordance with the preambles of claims 1, 2 or 19.

Known methods for analyzing the image contents of a test body are mainly based on metrics for determining similarities, such as distance measurements of segmented objects, or the calculation of global threshold distributions. These methods are based on translatorily invariable initial spectra. Situations often occur in reality, such as object displacements underneath the recording system, or different backgrounds during recording, or aliasing effects, so that in many cases a direct comparison of these initial spectra cannot be performed.

It is known from the reference book of Thomas TILLI, "Mustererkennung mit Fuzzy-Logik: Analysieren, klassifizieren, erkennen und diagnostizieren" [Pattern

Recognition by Means of Fuzzy Logic: Analyzing, Classifying, Determining and Diagnosing], Franzis-Verlag GmbH, München, publishers, 1993, pp. 183/184, 208 to 210, 235 to 257, to use fuzzy logic for image processing, wherein a spectral transformation can be one type of signal preparation.

In the technical article "Mustererkennung mit Fuzzy-Logik" [Pattern Recognition by Means of Fuzzy Logic] by Peter ARNEMANN, Elektronik 22/1992, pages 88 to 92, it is described how to perform pattern recognition by means of fuzzy logic.

The article by D. Charalampidis, T. Kasparis, M. Georgiopoulos, J. Rolland "A Fuzzy ARTMAP-Based Classification Technique of Natural Textures", Fuzzy Information Processing Society, 1999, NAFIPS, 18th International Conference of the North American, June 10 to 12 1999, pp. 507 to 511, describes the performance of pattern recognition with a training phase and the use of a window of 16 x 16 pixels for image recognition.

The object of the invention is based on providing methods for signal evaluation of an electronic image sensor in the course of pattern recognition of the image contents of a test body.

In accordance with the invention, this object is attained by the characteristics of claims 1, 2 or 19.

An advantage of the invention lies in particular in that a sensor signal is analyzed in an image window of the size of n x n pixels. As a result of this it is possible to consider the sensor signal of this image window to be local. The image analysis method in accordance with the invention can be divided into the substantial steps: characteristics formation, fuzzyfying, interference, defuzzyfying and decision regarding the class affiliation.

In the course of characteristics formation, the sensor signal is converted by means of at least one calculation specification into an invariant, in particular translation-invariant, signal in the characteristic space. It is the aim of the characteristics formation to define those values by means of which typical signal properties of the image content are characterized. The typical signal properties of the image content are represented by so-called characteristics. In this case the characteristics can be represented by values in the characteristic space, or by linguistic variables. A signal is created by transferring the sensor signal into the

characteristic space, which consists of one characteristic value or several characteristic values.

The affiliation of a characteristic value with a characteristic is described by at least one indistinct affiliation function. This is a soft or indistinct affiliation, wherein the affiliation of the characteristic value with the characteristic exists as a function of the characteristic value in a standardized interval between 0 and 1. The concept of the affiliation function leads to a characteristic value no longer totally, or not at all, being capable of being affiliated with a characteristic, but instead can take on a fuzzy affiliation, which is located between the Boolean logical functions 1 and 0. The just described step is called fuzzyfication. Thus, in the course of fuzzyfication a conversion of a definite characteristic value into one or several indistinct affiliations takes substantially place.

In connection with the interference, a higher order affiliation function is generated by means of a calculation specification consisting of at least one rule, wherein all affiliation functions are linked to each other. As a result,

a higher order affiliation function is therefore obtained for each window.

In connection with defuzzyfication, a number value, also called a sympathetic value, is determined from the higher order affiliation function formed during interference. In the course of the decision regarding class affiliation, a comparison of the sympathetic value with a previously fixed threshold value takes place, by means of which the affiliation of the window with a defined class is decided.

What type the characteristic values in the characteristic space are is of lesser importance for the principle of the invention. Thus, for example, in connection with time signals there is the possibility to set the mean value or the variance as characteristic values. If it is required of the evaluation process that it can process the image contents free of errors regardless of the respectively prevailing signal intensity, and if furthermore small, but permissible fluctuations in the image signal do not lead to interference, it is useful if the conversion of the sensor signal from the two-dimensional local space is performed by means of a two-dimensional spectral transformation, such as,

for example, a two-dimensional Fourier, or a two-dimensional Walsh, or a two-dimensional Hadamard, or a two-dimensional circular transformation. Invariant characteristic values are obtained by means of the two-dimensional spectral transformation. A further preferred embodiment consists in using the amount of the spectral coefficient obtained by the spectral transformation as the characteristic value.

In a preferred exemplary embodiment, the affiliation functions are unimodal potential functions, and the higher order affiliation function is a multimodal potential function.

In accordance with a further preferred exemplary embodiment, at least one affiliation function is parametrized. If the affiliation function has positive and negative slopes, it is advantageous if it is possible to determine the positive and negative slopes separately. An improved matching of the parameters to the data sets to be examined is assured by this.

In accordance with a particularly preferred exemplary embodiment, the method can be divided into a learning phase and a working phase. If the affiliation functions are parametrized, it is possible in the learning phase to

determine the parameters of the affiliation functions from measured data sets. In the learning phase, the parameters of the affiliation functions are adapted to so-called reference images, i.e. during the learning phase an affiliation of the characteristic values resulting from the reference images with the respective characteristics is derived by means of the affiliation functions and their parameters. In the subsequent work phase the characteristic values resulting from the now measured data sets are weighted with the affiliation functions whose parameters had been determined in the learning phase, from which an affiliation of the characteristic values of the now measured data sets with the corresponding characteristics is produced. By dividing the method into a learning and a work phase the parameters of the affiliation functions are determined by means of measured reference data sets, and in the subsequent work phase the measured data sets, which are to be tested, are weighted with the affiliation functions fixed during the learning phase and are evaluated.

In accordance with a further preferred exemplary embodiment at least one rule by means of which the

affiliation functions are linked with each other, is a conjunctive rule within the meaning of an IF ...THEN linkage.

A further preferred exemplary embodiment subdivides the generation of the higher order indistinct affiliation functions into the processing of the partial steps: premise evaluation, activation and aggregation. In this case, in the premise evaluation an affiliation value is determined for each IF portion of a rule, and during the activation an affiliation function is fixed for each IF ... THEN rule. Thereafter, during the aggregation, the higher order affiliation function is generated by superimposing all affiliation functions created during the activation.

In accordance with a further preferred exemplary embodiment, the sympathetic value determination is performed in particular in accordance with a main emphasis and/or maximum method.

Exemplary embodiments of the invention are represented in the drawings and will be described in greater detail in what follows.

Shown are in:

Fig. 1, a flow diagram of the signal evaluation method,

Fig. 2, a sympathetic curve,

Fig. 3a, a difference function of the power of D = 8

Fig. 3b, a difference function of the power of D = 4

Fig. 3c, a difference function of the power of D = 2

A flow diagram of the signal evaluation method to be described in what follows is shown in Fig. 1. With the method for signal evaluation of image contents of a test body, a grid of N x N windows 01 is placed over the entire image to be analyzed. Each window 01 here consists of n x n pixels 02. In the course of the image analysis, the signal from each window 01 is analyzed separately. As a result, the image content 03 of each window 01 can be considered to be local.

The two-dimensional image of the local space is transformed into a two-dimensional image in the frequency space by one or several spectral transformations. The spectrum obtained is called a frequency spectrum. Since this is a discrete spectrum in the present exemplary embodiment, the frequency spectrum is also discrete. The frequency spectrum is constituted by the spectral coefficients 06 -

also called spectral values 06 -.

In the next method step the amount formation 07 of the spectral values 06 takes place. The amount of the spectral values 06 is called spectral amplitude value 08. In the present exemplary embodiment, the spectral amplitude values 08 constitute the characteristic values, i.e. they are identical to the characteristic values.

A circular transformation is preferably used for the transformation. With the circular transformation the invariance properties can be adjusted via the transformation

coefficients. It is possible to set a translation invariance, as well as a reflection invariance, or an invariance in respect to different other permutation groups. In this way it is possible to utilize the above mentioned transformation for example in the reflection-variant variation for inspecting characters

(consider the differentiation between the numbers "9" and "6"). In the same way the reflection-invariant variation can be used for inspecting workpieces, since here it is not necessary in particular to make a differentiation between a reflected part and the original. It should be mentioned that the amount spectrum of the Fourier transformation is reflection-invariant.

These transformations work with real coefficient values. It is therefore not necessary to utilize a complex calculation as with the Fourier transformation.

The circular transformation is extremely tolerant even in the sub-pixel range in connection with any arbitrary displacements. Comparisons have shown that this circular transformation is superior to other known transformations in regard to displacements.

The number of work coefficients (characteristics, features) is small, because the spectral coefficients are again combined in groups.

The tolerance to displacements is created by the combination. Even if a signal runs partially out of a measurement field, the characteristics remain relatively stable. Tests have shown that stability is maintained, even

if the image contents lie outside of the measurement field by up to approximately 30%.

The characteristic selection 09 follows as a further method step; the aim of the characteristic selection 09 is to select the characteristics 11, which are characteristic for the image content 03 of the image to be analyzed. Characteristic spectral amplitude values 08, which define the characteristic 11 by their position in the frequency space and by their amplitude, are possible as characteristics 11, but also linguistic variables such as "gray", "black" or "white".

In the next following method step, the fuzzyfication 12, the affiliation of each spectral amplitude value 08 with a characteristics 11 is fixed by means of a soft or indistinct affiliation function 13, i. e. weighting is performed.

If it is intended during a learning phase to match the affiliation functions 13 to so-called reference data sets, it is useful if the affiliation functions 13 are parametrized monomodal, i.e. one-dimensional potential functions, wherein the parameters of the positive and negative slopes can be matched separately to the data sets to be examined. In the work phase which follows the learning phase, the data sets of the image content from which the characteristic values 08 of

the test images result are weighted with the respective affiliation functions 13 whose parameters had been determined in the previous learning phase. This means that for each characteristic 11 a sort of TARGET-ACTUAL comparison between the reference data set, expressed in the parameters of the affiliation function 13, and the data set of the test image takes place. A soft or indistinct affiliation between the respective characteristic value 08 and the characteristic 11 is made by means of the affiliation functions 13.

In the next method step, the interference 14, a conjunctive linkage 15 - also called aggregation 15 - of all affiliation functions 13 of the characteristics 11 takes place, so that a higher order affiliation function 16 is created.

The next method step, the defuzzyfication 17, determines a concrete affiliation or sympathetic value 18 from the higher order affiliation function 16. During the classification 19, this sympathetic value 18 is compared with a previously set threshold value 21, so that a classification statement can be made. The threshold value 21 is set either manually or automatically. Setting of the threshold value 21 takes also place during the learning phase.

During the classification, a numerical value is not assigned directly to a defined class by means of a true or

false statement, a unimodal function is set instead, which describes an affiliation with a true or false statement.

In the course of this the class affiliation is trained, i.e. the decision curves are taught by means of measured values determined during the process. The functions by means of which a degree of affiliation is determined, are called affiliation functions ZGF = $\mu(m_X)$. The calculated value of the affiliation function ZGF is called sympathetic value μ. Several affiliation functions ZGF are often used, which are further combined in the subsequent steps in order to achieve an unequivocal statement.

However, this is specifically not a neuronal network being used. It is known that neuronal networks can be trained.

The fuzzy plate classification is based on a concept which simultaneously provides a distance measurement and a characteristic linkage. The "fuzzy" fact here is that the characteristics are "rounded off", not logically, but indistinctly. For one, this leads to all characteristics being summarily considered. This means that small deviations from a characteristic are still tolerated. If secondly the deviation from a characteristic becomes too large, this has immediately a large effect on the distance measurement. Accordingly, the output of the classificator does not provide

a "good/bad" decision, but a continuous output value between [0 ... 1]. Thereafter a threshold value is used, which makes a "good/bad" decision possible.

The output value for the distance measurement (sympathetic value) is $\mu = 2^{-2}$, wherein

$$z=\frac{1}{M}\sum_{x=0}^{M-1}\left(\frac{|m_x-x_0(m_x)|}{C_x}\right)^D, 0\leq z\leq 10, z>10 \Rightarrow \mu(z)\equiv 0,$$

Here, the coefficients have the following meanings: x = counting index, z = averaged distance measurement, M = number of characteristics, x_0 = mean value of C_{diff}, C_x = expansion value, D = power, μ = sympathetic value, C_{diff} = difference measurement of the expansion value.

The expansion value C is taught with the aid of measured values which had been generated by means of the circular transformation.

The μ-value describes how close the similarity of a pattern is in relation to a reference pattern described by the characteristics. This means that the z-value takes over the actual control of the μ-value. If the z-value is very small, the μ-value is close to 1. The patterns are very similar (sympathetic). However, if the z-value is large, the

μ-value will become small, the patterns are not similar. The course of the curve - as implemented - is represented in Fig. 2.

Initially, in the learning phase the values $Cdiff_x$ are determined, namely for each characteristic m_x one value

$$Cdiff_x = \max(m_x) - \min(m_x)$$

wherein C_{diff} is the difference measurement of the expansion value, and m the characteristics.

During the inspection the learned C_{diff} values are used. The values can still be assigned an additional tolerance a. Settlement takes place during the running time:

$$C_x = (1 + 2\ p_{ce}) \quad \frac{\max(m_x) - \min(m_x)}{2}, \quad a = (1 + 2\ p_{ce})$$

wherein C is the expansion value and P_{ce} is the percental tolerance of C_{diff}.

The value range of a lies between [1 ... 3]. The value P_{ce} indicates the percental tolerance with which C_{diff} is respectively charged. A 50% expansion of the range of C_{diff} is intended to be achieved; in that case a = 1+2*0.5 = 2.

The x_o value indicates the mean value of C_{diff}; it is calculated for each characteristic during the running time.

The difference between the characteristic value and the mean characteristic value, which is determined from the value C_x, is calculated. This difference is standardized with the width of the expansion value C_x. The result is that with a slight deviation the corresponding characteristic contributes little to the z-value; however, with a large deviation a large deviation value will result as a function of the difference measure of the expansion value C_{diff}. The standardized difference is called d_x.

The power D (2, 4, 8) sets the sensitivity at the flanks of the standardized difference function d_x. If the value D is set to "infinity" - which is not technically possible - an infinite flank steepness is also obtained, and therefore a hard good/bad decision. Therefore the values are

customarily set to between 2 ... 20. The curves for the values 2, 4 and 8 are represented in Figs. 3c, 3b and 3a.

The exponentiated functions d_x are added up, however, only the number M of the characteristics m which have been switched on is used. Following the adding-up, the calculated value is divided by the number M. The mean value of all exponentiated differences d_x is determined.

The effect is the following: because of the exponentiation, small deviations will not be important, but large ones will be increased. A deviation of all characteristic differences is calculated by averaging. This has the result that even with the deviation of several characteristics the μ-value is not drastically lowered. This value will become very small only with larger deviations.

A threshold value evaluation follows thereafter.

$$\mu_{\text{klass}} = \begin{cases} \text{Good,} & \text{if } \mu(z) \geq \mu_S \\ \text{Error,} & \text{if } \mu(z) < \mu_S \end{cases}$$

This process is performed for all windows.

An evaluation of dynamic processes - such a printing processes - requires non-linear distance measurements (sympathetic values).

List of Reference Symbols

01	Window, N x N windows
02	n x n pixels
03	Image contents
04	2-dimensional spectral transformation, calculation specification
05	-
06	Spectral coefficient, spectral value
07	2-dimensional amount formation, calculation specification
08	Spectral amplitude value=characteristic value
09	Characteristics selection
10	-
11	Characteristic
12	Fuzzyfication
13	Affiliation function
14	Interference, calculation specification
15	-
16	Higher order affiliation function, linkage, aggregation
17	Defuzzyfication
18	Affiliation value, sympathetic value
19	Classification, class affiliation
20	-
21	Threshold value
C	Expansion value
C_{diff}	Difference measure of the expansion value
D	Power
M	Number of characteristics

ZGF	Affiliation function
a	Tolerance
d_x	Nominated difference
m	Characteristic
p_{ce}	Percental tolerance of C_{diff}
x	Counting index
z	Averaged distance measurement
μ	Sympathetic value, distance measurement